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Does A Virtuous Circle Really Exist? Revisiting the Causal Linkage Between CSP and CFP

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Abstract

Previous studies have proposed a virtuous circle between corporate social performance (CSP) and corporate financial performance (CFP). However, a key challenge researchers face when empirically examining this virtuous circle is endogeneity. In this paper, we apply a well-developed method—dynamic panel data (DPD) estimation—to account for endogeneity and conduct two studies to reexamine the causal relationship between CSP and CFP. Study 1 relies on KLD ratings from 1997 to 2012 as the measure of CSP. According to the results of Study 1, although CFP measured as ROE may have a causal impact on CSP, it is doubtful whether there is a causal influence of CSP on CFP. Study 2 relies on the sustainability scores provided by Sustainalytics from 2009 to 2018 as the measure of CSP. Study 2 reports that CSP does not causally influence CFP and that CFP does not have a causal impact on CSP. Together, Study 1 and Study 2, using different measures for CSP, suggest that a virtuous circle between CSP and CFP may not exist. Our study suggests that doing good may not necessarily lead to doing well and that doing well may not naturally result in doing good. Thus, our study implies that future studies should seriously consider the causal mechanisms through which CSP may influence or may be influenced by CFP. Our paper also discusses the implications for CSP research and for management and organization research. The limitations of applying DPD estimation to empirically examine the causal relationship between CSP and CFP are also discussed.

Keywords CSP–CFP relationship · Virtuous circle · Bidirectional causality · Endogeneity · Dynamic panel data (DPD) estimation

Introduction

The linkage between corporate social performance (CSP) and corporate financial performance (CFP) has been empirically examined for decades (for reviews, see Aguinis and Glavas 2012; Margolis and Walsh 2003). This literature proposes a virtuous circle between CSP and CFP (Surroca et al. 2010; Waddock and Graves 1997). The virtuous circle suggests bidirectional causality (Busch and Friede 2018), e.g., "improved CSP leads to better financial performance" and "better financial performance results in improved CSP" (Waddock and Graves 1997, p. 307). Previous studies have relied on multiple theories to explain this bidirectional causality. On the one hand, scholars mainly draw from instrumental stakeholder theory to explain why CSP causally affects CFP (Jones 1995). In this view, CSP can enhance CFP because CSP cultivates more cooperative, favorable, and enduring relationships with stakeholders, characterized by high levels of trust, cooperation, and information sharing (Jones et al. 2018). On the other hand, prior studies suggest that better CFP generates extra slack resources, which in turn are invested in socially responsible activities to enhance CSP (e.g., Chiu and Sharfman 2011; Waddock and Graves 1997). Despite the large number of previous studies, one key methodological challenge for establishing the virtuous circle is endogeneity because those studies mainly rely on archival and/or observational data, and the typical analytical approach is regression analysis (Mattingly 2015; Mattingly and Berman 2006). Unfortunately, endogeneity has yet to be fully addressed by these studies (Crane et al. 2017; Huang

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and Watson 2015). If endogeneity is not addressed, a causal relationship between CSP and CFP is difficult to establish. For example, it is uncertain whether CSP drives CFP, CFP impacts CSP or the significant correlation between CSP and CFP is driven by unobservable factors, such as R&D (McWilliams and Siegel 2000).

In this study, we discuss the causality between CSP and CFP. Examining the causality between CSP and CFP helps us more deeply understand not only whether CSP and CFP are correlated but also whether CSP causally affects CFP and vice versa. More specifically, we directly examine the bidirectional causality between CSP and CFP using dynamic panel data (DPD) estimation—the dynamic panel GMM estimator—a well-developed method to address endogeneity (Arellano and Bond 1991; Blundell and Bond 1998). Many studies in economics, finance, management, and marketing have adopted this method to address endogeneity and examine causal relationships (e.g., Alessandri et al. 2012; Arend et al. 2014; Fremeth and Shaver 2014; Gómez and Maícas 2011). Following studies that specifically show how to use DPD estimation (e.g., Roodman 2009a, b; Wintoki et al. 2012), we apply DPD estimation and conduct two studies using different measures for CSP (Mattingly 2015; Mattingly and Berman 2006). In addition to the DPD analyses, we conduct two other analyses (i.e., pooled OLS regression and fixed-effects regression) to highlight the potential problems of ignoring endogeneity (Wintoki et al. 2012).

Our empirical analyses reveal three findings regarding the causality between CSP and CFP. First, in Study 1 in which CSP is measured by KLD ratings, both pooled OLS regression and fixed-effects regression generally show that overall CSP is positively and bilaterally related to CFP, a finding consistent with previous studies (Surroca et al. 2010; Waddock and Graves 1997). However, the significant correlations reported by pooled OLS regression and fixed-effects regression should not be interpreted as evidence of causality between CSP and CFP because pooled OLS regression and fixed-effect regression do not address endogeneity.

Second, the DPD estimation of Study 1 yields interesting findings regarding the causality between CSP and CFP when endogeneity is addressed. On the one hand, DPD estimation reports that the relationship between overall CSP and CFP becomes neutral, i.e., the coefficient becomes non-significantly different from zero, when endogeneity is accounted for. These findings cast doubt on the positive causal influence of CSP on CFP. On the other hand, DPD estimation indicates that CFP measured by ROE is positively associated with overall CSP, implying that there might exist a causal influence of CFP. Third, Study 2 uses alternative measures of CSP (i.e., sustainability scores provided by Sustainalytics) to replicate the analyses of Study 1. The results of Study 2 suggest that a virtuous cycle between CSP and CFP may not exist.

Our study uses a well-developed method to examine the causal relationship between CSP and CFP and thereby contributes to the CSP literature. First, our study uses very similar data and measures as the large body of previous studies but finds different empirical results regarding the causal relationship between CSP and CFP. When endogeneity is not accounted for, we find empirical results consistent with bidirectional causality (Aguinis and Glavas 2012; Busch and Friede 2018; Margolis and Walsh 2003). However, when endogeneity is addressed by DPD estimation, we find empirical evidence that CFP may causally impact CSP but that CSP may not causally impact CFP. Therefore, in line with a few recent empirical findings that also report neutral CSP–CFP relationships (e.g., Lee et al. 2018; Zhao and Murrell 2016), our study suggests that future studies on the CSP–CFP relationships should focus more on specific mechanisms to explain the causal linkage between CSP and CFP, as well as particular conditions under which causal linkages may or may not exist.

Second, our study provides a new approach for addressing endogeneity in the estimation of the CSP–CFP relationship. When addressing endogeneity, one may want to use external instrumental variables. However, if the identification of valid external instrumental variables is difficult, an alternative approach suggested by our study is the DPD approach, in which lagged values of CSP and CFP are used as internal instrumental variables. The internal instrumental variables constructed by the DPD approach satisfy the validity requirements suggested by Bettis et al. (2014). Therefore, our study offers a feasible approach for addressing endogeneity when external instrumental variables are difficult to identify.

Our paper is organized as follows. First, we provide a brief review of the theories addressing the causal relationships between CSP and CFP. Second, we show three specific sources of endogeneity for the empirical estimation of CSP–CFP relationships. Third, we conduct two studies which apply DPD estimation to empirically explore the causal linkages between CSP and CFP. Finally, we discuss the implications and limitations of our paper.

Theories About the Causal Relationships Between CSP and CFP

In this section, we provide a review of previous studies on the causal linkages between CSP and CFP. As noted above, Busch and Friede's (2018) meta-analysis reports that the CSP–CFP relation is positive and bilateral, suggesting bidirectional causality between CSP and CFP. In other words, CSP can causally affect CFP, while CFP can also causally influence CSP. Thus, our review is divided into two parts. First, we review the theoretical mechanisms of the causal effect of CSP on CFP. Second, we review the theoretical mechanisms of the causal influence of CFP on CSP.

The Causal Influence of CSP on CFP

Previous studies examining the causal influence of CSP on CFP have mainly emphasized the business case for CSP; that is, CSP is good for business in ways that reflect directly on the bottom line (Wood 2010). To justify the business case for CSP, scholars have mainly relied on instrumental stakeholder theory to explain why CSP causally affects CFP (Jones 1995). The key theme of instrumental stakeholder theory is that CSP can enhance the competitive advantage of the firm because CSP cultivates more cooperative, favorable, and enduring relationships with stakeholders that are characterized by high levels of trust, cooperation, and information sharing (Jones et al. 2018). Drawing from instrumental stakeholder theory, previous studies have suggested that CSP can enhance CFP through many forms of stakeholder endorsements of the firm. Below, we present the most frequently proposed arguments.

First, CSP leads to enhanced reputation (Brammer and Pavelin 2006), which increases customer loyalty and trust (Vlachos et al. 2009), customer satisfaction and purchase intention (Luo and Bhattacharya 2006), and attractiveness to job candidates (Turban and Greening 1997). Second, in firms with improved CSP, employees show greater job satisfaction, present greater commitment to their firms, engage in more citizenship behaviors and have less turnover intention (for a recent meta-analysis, see Zhao et al. 2020). Third, closer relationships with firms make stakeholders more willing to share information with these firms, which can enhance firm innovation (Harrison et al. 2010; Tantalo and Priem 2016). For example, closer relationships with customers offer new knowledge that can be sources of innovation, and better relationships with employees can trigger innovation by encouraging employees to engage in innovative projects (Flammer and Kacperczyk 2016). Fourth, CSP reduces firm-specific risk and thus enhances CFP. Orlitzky and Benjamin's (2001) meta-analysis reports a negative relationship between CSP and firm risk. More recent studies also show that CSP is negatively related to stock price crash risk (Kim et al. 2014) and firm default risk (Verwijmeren and Derwall 2010). In addition, CSP can provide "insurance-like" protection for firms when bad acts occur (Godfrey 2005) and mitigate the negative impacts of bad acts because stakeholders are less likely to attribute responsibility for the bad acts to the firms (Godfrey et al. 2009; Koh et al. 2014).

The review above shows that previous studies have suggested many mediating mechanisms to explain the causal influence of CSP on CFP. However, in their review, Aguinis and Glavas (2012) indicate that only 7% of the studies addressing the outcomes of CSP empirically explored the mediating mechanisms. In most of those studies, the typical analytical approach was to directly regress measures of CFP on measures of CSP (Mattingly 2015). As we will show in the next section, the analytical approaches previously adopted have not addressed endogeneity, and thus, the direct causal linkage from CSP to CFP is difficult to establish.

The Causal Linkages from CFP to CSP

Compared with the studies addressing the causal influence of CSP on CFP, studies examining the causal linkages from CFP to CSP are relatively limited. In this literature, studies have mainly relied on slack resources theory to explain the causal influence of CFP on CSP. The main argument is that better CFP generates extra slack resources, which in turn are invested in socially responsible activities to enhance CSP (e.g., Buchholtz et al. 1999; Chiu and Sharfman 2011; Seifert et al. 2004; Waddock and Graves 1997).

However, the empirical results are mixed when different types of slack resources are taken into account. In one study, Surroca et al. (2010) report that better CFP generates intangible slack resources, such as innovation resources, human resources, reputation, and culture, which can further enhance CSP. Shahzad et al. (2016) suggest that the relationship between slack resources and CSP varies depending on the type of slack resources; in their study, Shahzad et al. (2016) report that human resources are positively related but financial resources and innovation resources are negatively related to CSP. In a study examining the CSP of sub-Saharan economies, Julian and Ofori-Dankwa (2013) also report that the greater the financial resources sub-Saharan African firms have, the less CSP they will present. Zhang et al. (2018) analyze the CSP of publicly listed US multinational companies and report that financial resources are positively related to CSP, while human resources are negatively related to CSP. Furthermore, those studies directly regressed measures of CSP on measures of CFP or slack resources and did not address endogeneity; therefore, the causal linkage from CFP to slack sources and then to CSP is hard to establish.

The Sources of Endogeneity

According to our review above, previous studies have argued that CSP can causally affect CFP through multiple mediating mechanisms and that CFP can also have a causal influence on CSP due to the slack resources accrued by better CFP. In this regard, Busch and Friede (2018) argue that there is a virtuous circle between CSP and CFP (Surroca et al. 2010). The virtuous circle implies a mutual influence between CSP and CFP, which may lead to endogeneity in the empirical estimation of the CSP–CFP relationship. However, few studies have considered endogeneity, although the CSP–CFP relationship has been empirically examined in many studies. Here, we discuss the sources of endogeneity in the estimation the CSP–CFP relationship. Endogeneity can arise from three sources when the causal effect of CSP on CFP is empirically examined.[1]

First, endogeneity can be caused by simultaneous causality. As causality between CSP and CFP runs in both directions, simultaneous causality is present (Bascle 2008). In other words, the CSP–CFP relationship reflects a feedback loop: CSP affects CFP, while CFP also influences CSP at the same time (Surroca et al. 2010; Waddock and Graves 1997).

Second, endogeneity arises due to omitted variable bias (Bascle 2008). In the empirical examination of the CSP–CFP relationship, an omitted variable bias occurs when variables (e.g., R&D intensity) that can affect both CSP and CFP are omitted. The positive CSP–CFP relationship becomes neutral when such a variable is included (McWilliams and Siegel 2000). In addition to R&D intensity, other omitted variables can result in this endogeneity problem. For example, CEOs' personal values can influence both CSP and CFP (Agle et al. 1999). Thus, a positive CSP–CFP relationship might be overestimated because both CSP and CFP can be driven by CEO personality or values.

The third source of endogeneity is the dynamic nature of the CSP–CFP relationship (Wintoki et al. 2012). Specifically, a strong exogeneity assumption that has often been implied by previous studies is that current values of CSP are independent of past values of CFP. However, this assumption is not realistic. Indeed, some prior studies have shown that current values of CSP and past values of CFP are correlated (Surroca et al. 2010). In fact, previous studies have generally concluded that better past CFP accumulates slack resources, with which a firm can make more investments in social issues, thereby enhancing its current CSP (e.g., Seifert et al. 2004). Some researchers even contend that only firms acquiring significant slack resources are able to behave responsibly (Roberts 1992). In sum, CSP is endogenous with respect to CFP because past CFP is related to current CSP.

[1] In addition to the three sources discussed above, endogeneity may potentially exist when the sample is truncated and a sample-selection bias is present (Clougherty et al. 2016). We argue, however, that sample-selection bias may not manifest in our study because our sample is constructed based on a large dataset of third-party CSP ratings (i.e., KLD ratings). Firms are unable to decide whether they are selected to be rated by KLD; instead, KLD ratings cover over 3000 large US firms. Thus, we argue that the sample is unlikely to be truncated.

Study 1: Dynamic Panel Data (DPD) Estimation Using KLD Ratings

Above, we discussed the three sources of endogeneity in the empirical examination of the CSP–CFP relationship. In Study 1, we apply DPD estimation to address endogeneity and to empirically explore the causal relationships between CSP and CFP. Study 1 relies on KLD ratings to measure CSP.

Sample and Data Sources

Peloza's (2009) review suggests that a substantial body of studies has used KLD ratings to measure CSP (see also Mattingly 2015). Recent studies have continued to use KLD ratings to measure CSP (Koh et al. 2014; Luo, Wang et al. 2015). To ensure that our analyses are comparable to previous studies, we adopt the data and measures used by previous studies. Thus, we rely on the KLD database as the source of measures on CSP. Our initial sample consisted of KLD ratings from 1997 to 2012. CFP data are obtained from Compustat. Data for some control variables (e.g., firm size, firm leverage, slack resources, and top executive pay) are also obtained from Compustat. Data for other control variables are obtained from CRSP, Risk Metrics, and Thomson Reuters. After the deletion of several duplicate records and missing values, the final sample contains 992 US listed firms and 9028 firm-year observations from 1997 to 2012.

Measures

CSP

Following previous studies (e.g., Choi and Wang 2009), we use five KLD categories to construct an aggregate measure of CSP. These five KLD categories are *Community*, *Employee Relations*, *Diversity*, *Environmental Performance*, and *Product*. According to Hillman and Keim (2001), these categories parallel a firm's primary stakeholder groups: employees (categories of *Employee Relations* and *Diversity*), customers (category of *Product*), the community (category of *Community*), and the natural environment (category of *Environmental Performance*). Typically, KLD ratings use strengths to represent positive aspects of CSP and concerns to reflect negative aspects of CSP. Several rating items are used to evaluate the strengths and concerns of each category. For each rating item within one category, KLD codes it as a dummy variable to indicate whether a firm in a given year has initiated activities or practices as rated by this item. In this way, the sum of the rating items of strengths is the score of strengths of the category, and the sum of the rating items of concerns is the score of concerns of the category.

Table 1 Variables and measures

Variable	Measure
1. ROA	The ratio of net income over total assets
2. ROE	The ratio of net income over total equity
3. Tobin's *Q*	Tobin's *Q* is calculated as: (equity market value + debt market value)/(equity book value + debt book value)
4. Leverage	The ratio of total debt over total equity
5. Firm size	The natural logarithm of total sales
6. R&D intensity	The ratio of R&D expense over total sales
7. R&D dummy	Coded as 1 if missing values of R&D expense were replaced by zeros, and 0 otherwise
8. Firm risk	Firm beta
9. Institutional ownership	The percentage of shares owned by institutional investors to total shares outstanding
10. Executive total compensation	The natural logarithm of the sum of total compensation of all executives listed in Compustat
11. Executive long-term compensation	The percentage of executives' total long-term compensation (including stock options, granted stocks, and long-term incentive plans) to their total compensations
12. Advertising intensity	The ratio of advertising expenses over total sales
13. Advertising dummy	Coded as 1 if missing values of advertising expense were replaced by zeros, and 0 otherwise
14. Board independence	The ratio of the number of independent directors to the number of all directors
15. CEO duality	Coded as 1 if a CEO also took the position of board chair and 0 otherwise
16. Slack resources	The ratio of the sum of cash flow from a firm's operating, financing, and investing activities over total assets
17. SOX dummy	Coded as 1 if the year is 2002 or later and 0 otherwise
18. Financial crisis dummy	Coded as 1 if the year is 2008 or later and 0 otherwise
19. Overall CSP_KLD	An overall score of five KLD ratings
20. Positive CSP	An aggregate score of five KLD strength ratings
21. Negative CSP	An aggregate score of five KLD concern ratings
22. Overall CSP_SUS	Sustainability scores from Sustainalytics database, 2009–2018

Furthermore, the items provided by KLD representing strengths differ from the items representing concerns; consequently, CSP strengths are not directly comparable to CSP concerns. Similarly, the number of rating items differs across the five categories. To address these limitations, we compute the standardized scores of strengths and concerns for all five KLD categories. We apply this standardizing process for all KLD data from 1991 to 2012. This approach ensures that the scores of KLD categories are comparable because each category has an equal weight when the scores of each category are added to generate an aggregate score (Choi and Wang 2009). For example, we add all strength items from the KLD *Community* category to obtain a raw score; then, the raw score is subtracted from the overall mean of the raw score and divided by the standard deviation of the raw score (Mattingly and Berman 2006). The resulting standardized score represents the standardized community strengths. In the same way, we create a standardized score to reflect standardized community concerns by using concerns from the *Community* category. The same procedure is applied to the four other KLD dimensions (i.e., *Employee Relations*, *Diversity*, *Environmental Performance*, and *Product*). As a result, we generate five standardized strength scores and another five standardized concern scores. Subsequently, we use the sum of the five strength scores to represent *positive CSP* and the sum of the five concern scores to reflect *negative CSP*. Next, we create an *overall CSP* measure by subtracting positive CSP from negative CSP. The three CSP measures have been used by many previous studies (e.g., Choi and Wang 2009). Specifically, we use the following formulas to compute *positive CSP*, *negative CSP*, and *overall CSP*:

$$
\begin{aligned}
Positive\ CSP = {} & Community\_Strengths_{standardized} \\
& + Employee\_Relations\_Strengths_{standardized} \\
& + Diversity\_Strengths_{standardized} \\
& + Environmental\_Performance\_Strengths_{standardized} \\
& + Product\_Strengths_{standardized}
\end{aligned}
$$

$$
\begin{aligned}
Negative\ CSP = {} & Community\_Concerns_{standardized} \\
& + Employee\_Relations\_Concerns_{standardized} \\
& + Diversity\_Concerns_{standardized} \\
& + Environmental\_Performance\_Concerns_{standardized} \\
& + Product\_Concerns_{standardized}
\end{aligned}
$$

Overall CSP = Positive CSP − Negative CSP

Table 1 lists all variables in this study and their measures.

CFP

Previous studies have operationalized CFP as ROA, ROE, and Tobin's *Q* (e.g., Luo and Bhattacharya 2006; Surroca et al. 2010). While ROA and ROE reflect past accounting performance, Tobin's *Q* reflects financial market performance that represents shareholders' perceptions of a firm's future financial returns (Keats 1988). As noted by Huang and Watson (2015), accounting performance measures are more suitable for examining the CSP–CFP relationship because shareholder perceptions of CSP vary substantially. In fact, the CSP–CFP relationship will be distorted if CSP is measured by financial market performance because some shareholders value CSP and other shareholders unduly devalue CSP (Martin and Moser 2016). Therefore, in this paper, we use ROA as the primary measure of CFP (Waddock and Graves 1997). ROA is computed as the net income over total assets. For a robustness check, two alternative measures of CFP—ROE and Tobin's *Q*—are used in supplemental analyses.

Control Variables

One critical issue of DPD estimation is that the empirical model should include as many time-varying control variables affecting both CSP and CFP as possible (Hansen and Singleton 1982). Therefore, we control for variables found by prior studies to affect both CSP and CFP. However, we acknowledge that it is impossible for us to control for all time-varying variables that can potentially affect both CSP and CFP. We will discuss this limitation in the last section of this paper.

R&D investments and advertising expenses are critical to the relationships between CSP and CFP (McWilliams and Siegel 2000). Hence, we control for *R&D intensity*. For firms with missing R&D data, we replace the missing values with zeroes and then create a dummy variable (*R&D dummy*) to reduce estimation bias (Uotila et al. 2009). *Advertising intensity* is also controlled. For firms with missing data on advertising expenses, we replace the missing values with zeroes and generate a dummy variable (*Advertising dummy*) to reduce estimation bias. Studies show that capital structure is related to both CSP and CFP (Waddock and Graves 1997); thus, we control for *firm leverage*. Slack resources have also been found to affect both CSP (Seifert et al. 2004) and CFP (Daniel et al. 2004). Therefore, *slack resources* are included as a control variable. *Firm size* is controlled because it can affect both CSP and CFP (Orlitzky 2001). *Firm risk* is also controlled because it has been found to be correlated with CSP (Luo and Bhattacharya 2009) and CFP (Bettis and Mahajan 1985).

Previous studies have shown that CSP is associated with corporate governance variables (e.g., Deckop et al. 2006; Jo and Harjoto 2012; Johnson and Greening 1999). Previous studies have also reported that corporate governance affects CFP (Finkelstein and D'Aveni 1994). Therefore, we control for several corporate governance variables because they likely influence both CSP and CFP. These variables include *board independence*, *institutional ownership*, *executive total compensation*, *executive long-term compensation*, and *CEO duality*.

In addition, we construct a set of *industry dummy variables* based on a one-digit SIC to control for industry-fixed effects. Finally, we construct a set of *year dummy variables* to control for year-fixed effects. We also create a dummy variable to control for the impact of SOX in 2002 and another dummy variable to control for the impact of the global financial crisis in 2008. Moreover, several variables, including CFP measures and control variables, contain some outliers, such as extremely large or extremely small values. Rather than excluding those outliers, we *Winsorize* those distributions at the top and bottom 1st percentiles (Gentry and Shen 2013).

DPD Estimation Method

DPD estimation can address other methodological issues in addition to endogeneity in the empirical estimation of the CSP–CFP relationship. First, it can address fixed effects, removing them by first differencing (Arellano and Bond 1991). Second, it can address autocorrelations by instrumenting the first-differenced lagged dependent variable with its historical values (Arellano and Bond 1991). Autocorrelation is a salient methodological issue in studies of the CSP–CFP relationship because the autocorrelation of KLD ratings—the measures of CSP in this study—is as high as 53%–71% (Bansal et al. 2016). Third, DPD estimation is especially useful for panel datasets with a large panel dimension (i.e., the number of firms > 100) and a short time dimension (i.e., the number of years < 30). Our sample is composed of 992 firms during a period of approximately 15 years (1997–2012). In this case, the correlations of the lagged CFP with the error terms are significant, resulting in biased estimation; however, this methodological issue can be addressed by DPD estimation (Roodman 2009b).

To apply DPD estimation, we follow the approaches recommended by Roodman (2009a, b) to specify our estimation models. First, we use system GMM (instead of difference GMM) because system GMM increases efficiency. In addition, two-step GMM estimation is more efficient than one-step GMM estimation (Arellano and Bond 1991). Thus, we use two-step system GMM estimation. However, because two-step system GMM uses more instrumental variables than two-step difference GMM, it may not be appropriate to use two-step system GMM with a dataset that contains an extremely small number of firms.[2] A large number of instrumental variables and a small number of firms will cause GMM estimation to be unreliable, a problem referred to as "too many instruments" (Roodman 2009a). To avoid this problem, Roodman (2009a) recommends constraining the number of instrumental variables to ensure that it is smaller than the number of firms. We follow this recommendation in this paper.

To reduce the number of instrumental variables, we follow Roodman's (2009b) recommendation to "collapse" instrumental variables. Our preliminary analysis showed that doing so can decrease the number of instrumental variables from more than 3000 to less than 400. In addition, we carefully specify the lags used to instrument endogenous variables to ensure that the number of instrumental variables is smaller than the number of firms. We rely on the Hansen *J*-test to assess whether the instrumental variables are exogenous and valid. The Hansen *J*-test is robust to heteroskedasticity but becomes unreliable when too many instrumental variables are used (Roodman 2009a). As noted above, after we "collapse" instrumental variables and carefully specify the lags, there are fewer instrumental variables than firms. Therefore, we argue that the results of the Hansen *J*-test are robust, not weakened by too many instrumental variables.

Second, the standard errors of two-step GMM estimation are substantively downward biased. To avoid this problem, we use the robust estimator developed by Windmeijer (2005) for the two-step GMM estimation. Third, the Arellano-Bond test for autocorrelations (i.e., AR test) is biased if there are correlations across firms due to idiosyncratic disturbances (Arellano and Bond 1991; Roodman 2009b). Thus, year dummies are included to ensure the validity of the Arellano-Bond test for autocorrelations (Roodman 2009b). Since our panel dataset contains gaps, we use orthogonal transformation instead of difference transformation, increasing the efficiency of the DPD estimation and maximizing the sample size (Arellano and Bover 1995; Roodman 2009b).

Despite the advantages, it is worth noting that DPD estimation relies on several assumptions, which should be rigorously tested. The first assumption is that there is no serial correlation in the error term. If this assumption does not hold, the relevance of the instrumental variables should be questioned. The second assumption suggests that a firm's past CFP and traits are exogenous to the current CFP. Following Wintoki et al. (2012), we use two tests to examine this assumption. First, a second-order serial correlation test examines whether enough lags have been included to capture the dynamic CSP–CFP relationship. If adequate lags have been included, historical values of CFP beyond these lags can be used as valid instrumental variables because they are exogenous to the current CFP. More specifically, if this assumption holds, serial correlation in first differences (AR(1)) should exist, but serial correlation in second differences (AR(2)) should not exist (Arellano and Bond 1991). In addition, the Hansen overidentification test is used to examine the validity of the instrumental variables. In DPD estimation, multiple lags are used as instrumental variables, suggesting that this estimation model may be overidentified; thus, the test of overidentification should be conducted.

To summarize, we use two-step system GMM estimation with Windmeijer's (2005) correction to estimate the relationship between CSP and CFP. We treat all control variables (except dummy variables for industry and year, and for SOX in 2002 and the global financial crisis in 2008) as endogenous because, as we have noted above, they are correlated with both CSP and CFP. Dummy variables for industry and year, and for SOX in 2002 and the global financial crisis in 2008 are treated as strictly exogenous. The empirical analyses are conducted using *STATA* 13.1 with the command "xtabond2" (Roodman 2009b).

Analytical Procedures

We follow Wintoki et al.'s (2012) recommendations to apply DPD estimation to examine the causal relationships between CSP and CFP. The DPD analyses are divided into two parts. In the first part, our analyses include three steps to examine the causal influence of CSP on CFP: (1) examine the needed lags for the dynamic CSP–CFP relationship; (2) examine whether current values of CSP are strongly correlated with past values of CFP; and (3) apply DPD estimation to the relationship between CSP and CFP and examine the validity of the instrumental variables (Wintoki et al. 2012). As suggested by Wintoki et al. (2012), the first part also includes two additional analyses (i.e., pooled OLS and fixed-effects regression) to compare the results of DPD estimation with the results yielded by traditional estimation methods. In the second part, we repeat the three steps to address the causal influence of CFP on CSP.

Empirical Results of Study 1

The Causal Influence of CSP on CFP

In this section, we present the empirical results examining the causal influence of *overall CSP* on CFP. To demonstrate the three steps of DPD estimation, we first use ROA as the

[2] Our sample contains 992 firms, so we could argue that the number of firms is not extremely small.

Table 2 Descriptive statistics and correlations

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1. ROA	0.05	0.07																					
2. ROE	0.11	0.18	0.72																				
3. Tobin's Q	1.75	0.91	0.53	0.31																			
4. Leverage	3.36	2.61	− 0.23	0.01	− 0.22																		
5. Firm size	3.43	0.51	0.07	0.13	− 0.02	0.19																	
6. R&D intensity	0.02	0.04	0.00	− 0.03	0.26	− 0.14	0.00																
7. R&D dummy	0.49	0.50	− 0.10	− 0.05	− 0.22	0.23	0.02	− 0.39															
8. Firm risk	1.12	0.50	− 0.18	− 0.16	− 0.12	0.01	− 0.10	0.00	− 0.01														
9. Institutional ownership	0.74	0.16	0.01	− 0.04	− 0.04	− 0.18	− 0.09	− 0.02	− 0.12	0.24													
10. Executive total compensation	0.01	0.01	0.06	0.01	0.21	− 0.13	− 0.61	0.04	− 0.04	0.11	0.17												
11. Executive long-term compensation	0.53	0.27	0.20	0.20	0.16	− 0.02	0.22	0.03	− 0.05	0.05	0.28	0.23											
12. Advertising intensity	0.01	0.02	0.12	0.08	0.22	− 0.01	0.09	0.03	− 0.11	− 0.09	− 0.02	− 0.04	0.00										
13. Advertising dummy	0.34	0.47	0.08	0.05	0.16	0.04	0.05	0.06	− 0.15	− 0.03	0.02	− 0.02	0.01	0.69									
14. Board independence	0.74	0.15	− 0.02	0.02	− 0.09	0.05	0.14	0.04	− 0.06	− 0.01	0.20	− 0.10	0.22	− 0.05	− 0.05								
15. CEO duality	0.72	0.45	− 0.02	0.02	0.00	0.10	0.20	0.00	0.02	− 0.07	− 0.11	− 0.13	− 0.07	0.01	0.00	0.06							
16. Slack resources	0.07	0.08	0.16	0.04	0.29	− 0.21	− 0.13	0.24	− 0.11	0.11	0.15	0.16	0.05	0.09	0.12	0.01	− 0.10						
17. SOX dummy	0.76	0.43	− 0.03	− 0.04	− 0.15	− 0.07	− 0.15	− 0.05	0.01	0.21	0.38	0.17	0.32	− 0.03	0.03	0.28	− 0.17	0.12					
18. Financial crisis dummy	0.31	0.46	− 0.04	− 0.05	− 0.11	− 0.05	− 0.06	− 0.04	− 0.01	0.10	0.22	0.08	0.29	− 0.02	0.02	0.27	− 0.19	0.12	0.38				
19. Overall CSP_KLD	0.48	4.45	0.10	0.11	0.16	0.07	0.13	0.19	− 0.12	− 0.10	− 0.07	− 0.07	0.08	0.16	0.12	0.06	0.02	0.07	− 0.09	0.11			
20. Positive CSP	1.23	4.28	0.07	0.11	0.10	0.12	0.46	0.22	− 0.12	− 0.12	− 0.15	− 0.25	0.17	0.15	0.09	0.19	0.12	0.02	− 0.03	0.11	0.69		

Table 2 (continued)

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
21. Negative CSP	0.75	3.45	− 0.04	− 0.01	− 0.08	0.06	0.41	0.03	0.01	− 0.02	− 0.10	− 0.22	0.11	− 0.02	− 0.04	0.16	0.12	− 0.07	0.08	0.01	− 0.43	0.35	
22. Overall CSP_SUS[a]	55.68	8.34	0.06	0.12	− 0.01	0.02	0.32	0.28	− 0.13	− 0.15	− 0.22	− 0.22	0.16	0.10	0.01	0.19	0.02	0.00			0.52	0.57	0.07

$N=9028$; $p<0.05$ if $|r|>0.02$

[a] $N=1573$

measure for CFP. Descriptive statistics and correlations of variables are reported in Table 2. Positive CSP has a mean of 1.23 and a standard deviation of 4.28, while negative CSP has a mean of 0.75 and a standard deviation of 3.45. Given that positive CSP (or negative CSP) is computed as the aggregated scores of standardized strength (or concern) scores, it is not surprising that the mean of positive CSP (or negative CSP) would be smaller than the standard deviation. In addition, because overall CSP is computed as the difference between positive CSP and negative CSP, it is as expected that the mean of overall CSP is smaller than both positive CSP and negative CSP. We also note that overall CSP is positively related to positive CSP ($r=0.69$) and negatively related to negative CSP ($r=-0.43$), consistent with our approaches to compute those measures. We also note a positive relationship between positive CSP and negative CSP ($r=0.35$). Furthermore, overall CSP is positively related to the sustainability scores ($r=0.52$) used in Study 2, suggesting that it is reasonable for us to use sustainability scores as an alternative measure of overall CSP.

Step (1): Examine the Needed Lags for the Dynamic CSP–CFP Relationship

According to Wintoki et al. (2012), a critical aspect of DPD estimation is knowing how many lags are needed to estimate the dynamic relationship. That is, all older lags are assumed to be exogenous. As a result, they can be instrumental variables. Some studies propose that two lags are sufficient (e.g., Gschwandtner 2005). However, there is no strict rule to determine the necessary lags. To determine the lags that are needed, we follow Wintoki et al.'s (2012) recommendation and regress current CFP on six lags of past CFP, controlling for other firm characteristics and industry- and year-fixed effects. Table 3 shows the regression results. The regression results suggest that four lags of past ROA are enough to capture the dynamics of the CSP–CFP relationship. In Model 1, the p values of the coefficients of the first four lags of ROA are less than 0.05, while those of the older lags are greater than 0.05. In Model 2, the first four lags of ROA are dropped, and the p values of the coefficients of the older lags become 0.000. Such regression results indicate that the information contained by older lags is already included in the more recent lags.

Step (2): Examine Whether Current Values of CSP are Strongly Correlated with Past Values of CFP

One critical premise of the dynamic CSP–CFP relationship is that current values of CSP are correlated with past CFP values. We can directly examine this premise by two sets of regression analyses (Wintoki et al. 2012). First, we regress

Table 3 Regression results of current ROA on past values of ROA

	Model 1 DV = ROA			Model 2 DV = ROA		
	Coef	SE	p	Coef	SE	p
DV ($t-1$)	0.42	0.02	0.000			
DV ($t-2$)	0.04	0.02	0.034			
DV ($t-3$)	0.07	0.02	0.000			
DV ($t-4$)	0.03	0.02	0.039			
DV ($t-5$)	0.02	0.02	0.378	0.13	0.02	0.000
DV ($t-6$)	0.05	0.02	0.001	0.12	0.02	0.000
Constant	0.02	0.01	0.054	0.05	0.01	0.000
Leverage	0.00	0.00	0.000	0.00	0.00	0.000
Firm size	0.01	0.00	0.000	0.01	0.00	0.000
R&D intensity	− 0.17	0.03	0.000	− 0.23	0.03	0.000
R&D dummy	0.00	0.00	0.399	0.00	0.00	0.673
Firm risk	− 0.01	0.00	0.000	− 0.02	0.00	0.000
Institutional ownership	0.00	0.01	0.593	0.00	0.01	0.773
Executive total compensation	0.25	0.11	0.026	0.32	0.12	0.009
Executive long-term compensation	0.04	0.00	0.000	0.06	0.00	0.000
Advertising intensity	− 0.03	0.05	0.577	0.05	0.06	0.409
Advertising dummy	0.00	0.00	0.549	0.00	0.00	0.436
Board independence	0.01	0.00	0.216	0.00	0.00	0.643
CEO duality	0.00	0.00	0.022	0.00	0.00	0.059
Slack resources	0.08	0.01	0.000	0.10	0.01	0.000
Year-fixed effects	Included			Included		
Industry-fixed effects	Included			Included		
F (p value)	148.98 (0.000)			94.03 (0.000)		
R^2	40.02%			23.97%		

Table 4 Regression results of CSP at year t on ROA at year $t-1$

	Model 1 DV = CSP, IV = ROA			Model 2 DV = ΔCSP, IV = ROA		
	Coef	SE	p	Coef	SE	p
ROA ($t-1$)	5.08	0.82	0.000	0.87	0.44	0.049
Leverage ($t-1$)	0.07	0.02	0.002	0.00	0.01	0.937
Firm size ($t-1$)	0.57	0.13	0.000	0.45	0.08	0.000
R&D intensity ($t-1$)	18.79	1.79	0.000	1.95	0.84	0.021
R&D dummy ($t-1$)	− 0.26	0.12	0.028	0.05	0.07	0.462
Firm risk ($t-1$)	− 0.42	0.10	0.000	0.04	0.06	0.558
Institutional ownership ($t-1$)	− 0.96	0.33	0.003	− 0.02	0.20	0.935
Executive total compensation ($t-1$)	− 26.09	7.06	0.000	11.01	4.75	0.020
Executive long-term compensation ($t-1$)	0.96	0.23	0.000	− 0.02	0.13	0.856
Advertising intensity ($t-1$)	40.04	4.42	0.000	1.96	2.68	0.466
Advertising dummy ($t-1$)	0.06	0.14	0.688	0.02	0.09	0.832
Board independence ($t-1$)	1.47	0.30	0.000	0.39	0.19	0.042
CEO duality ($t-1$)	0.33	0.10	0.001	0.06	0.07	0.344
Slack resources ($t-1$)	1.92	0.58	0.001	− 0.52	0.35	0.139
Constant	− 7.88	1.04	0.000	− 1.47	0.71	0.038
Year-fixed effects	Included			Included		
Industry-fixed effects	Included			Included		
F (p value)	40.59 (0.000)			10.61 (0.000)		
R^2	18.55%			6.74%		

Table 5 Regression results of ROA at year t on CSP at year $t+1$

	Model 1 DV = ROA		
	Coef	SE	p
Overall CSP_KLD ($t+1$)	0.001	0.000	0.003
Leverage ($t+1$)	0.00	0.00	0.049
Firm size ($t+1$)	0.02	0.01	0.117
R&D intensity ($t+1$)	0.15	0.05	0.005
R&D dummy ($t+1$)	0.01	0.01	0.199
Firm risk ($t+1$)	− 0.02	0.00	0.000
Institutional ownership ($t+1$)	0.01	0.01	0.714
Executive total compensation ($t+1$)	0.00	0.19	0.993
Executive long-term compensation ($t+1$)	0.02	0.00	0.000
Advertising intensity ($t+1$)	0.48	0.20	0.018
Advertising dummy ($t+1$)	0.00	0.00	0.800
Board independence ($t+1$)	0.01	0.01	0.468
CEO duality ($t+1$)	0.00	0.00	0.081
Slack resources ($t+1$)	− 0.03	0.02	0.083
CSP (t)	0.00	0.00	0.226
Leverage (t)	0.00	0.00	0.000
Firm size (t)	− 0.01	0.01	0.237
R&D intensity (t)	− 0.35	0.05	0.000
R&D dummy (t)	− 0.01	0.01	0.218
Firm risk (t)	− 0.01	0.00	0.000
Institutional ownership (t)	− 0.03	0.01	0.016
Executive total compensation (t)	0.59	0.16	0.000
Executive long-term compensation (t)	0.04	0.00	0.000
Advertising intensity (t)	− 0.32	0.21	0.126
Advertising dummy (t)	0.00	0.00	0.580
Board independence (t)	0.00	0.01	0.779
CEO duality (t)	− 0.01	0.00	0.003
Slack resources (t)	0.13	0.02	0.000
Constant	0.08	0.01	0.000
Year-fixed effects	Included		
Industry-fixed effects	Included		
F (p value)	62.10 (0.000)		
R^2	24.60%		

lagged values of ROA and other firm characteristics on the current level of CSP at year t. Second, another regression analysis is conducted by regressing lagged values of ROA and other firm characteristics on the change in CSP from year t to year $t-1$. Industry and year effects are included in both regression analyses.

Table 4 shows the regression results. Model 1 reports that current CSP at year t is positively associated with past ROA at year $t-1$ ($b=5.08$, $p=0.000$). Model 2 demonstrates that the change in CSP from year $t-1$ to year t is positively associated with past ROA at year $t-1$ ($b=0.87$, $p=0.049$). Such results confirm the premise that current CSP is correlated with past CFP (e.g., Waddock and Graves 1997).

In line with Wintoki et al. (2012), we also adopt the approach recommended by Wooldridge (2010: 254) to examine the premise noted above. Table 5 shows the regression results. Model 1 reports that current ROA at year t is positively associated with future CSP at year $t+1$ ($b=0.001$, $p=0.003$). According to Wooldridge (2010: 299), "strict exogeneity rules out certain kinds of feedback" from current ROA to future values of CSP. Therefore, these results offer strong evidence that CSP is not strictly exogenous to ROA, confirming the premise that current values of CSP are correlated with past values of CFP.

Step (3): Apply DPD Estimation to the Relationship Between CSP and CFP and Examine the Validity of the Instrumental Variables

Table 6 reports the empirical results when CFP is measured as ROA. Both pooled OLS regression ($b=0.001$, $p=0.000$) and fixed-effects regression ($b=0.001$, $p=0.014$) show a positive association between overall CSP and ROA. However, DPD estimation indicates a substantially different relationship ($b=0.000$, $p=0.779$). This finding shows that overall CSP may not have a causal impact on ROA when endogeneity is accounted for by DPD estimation.

We also conduct specification tests of the DPD estimation. The AR(2) test shows a z-statistic of 1.09 and a p value of 0.278, indicating that a significant second-order serial correlation may not exist. The Hansen J-test yields a J-statistic of 76.77 and a p value of 0.084, indicating that the instrumental variables are valid and exogenous. In addition, we test the assumption of system GMM estimation that correlations between endogenous variables and unobservables do not vary over time (Roodman 2009b). To examine this assumption, we use a difference-in-Hansen test (Eichenbaum et al. 1988). This test yields a J-statistic of 15.52 and a p value of 0.562, suggesting that this assumption holds. As noted above, DPD estimation may have a problem of "too many" instrumental variables (Roodman 2009a). Specifically, Hansen J-tests become unreliable when there are "too many" instrumental variables. Here, we specifically use two lags (i.e., the fifth and sixth lags), such that the number of instruments (116) is much smaller than the number of firms (992). Therefore, the results of the Hansen J-tests are robust, not weakened by the problem of "too many" instrumental variables.

Alternative Measures of CSP

We employ a set of alternative measures of CSP. We first divide CSP into positive CSP and negative CSP and then reconduct the analyses as shown above. According to

Table 6 Empirical results of the causal influence of CSP on CFP

Independent variable	*DV* = *ROA*			*DV* = *ROE*			*DV* = Tobin's *Q*		
	b	Robust SE	*p*	*b*	Robust SE	*p*	*b*	Robust SE	*p*
Pooled OLS regression									
Overall CSP_KLD	0.001	0.000	0.000	0.002	0.000	0.000	0.015	0.002	0.000
Positive CSP	0.001	0.000	0.000	0.002	0.001	0.000	0.014	0.002	0.000
Negative CSP	− 0.001	0.000	0.000	− 0.003	0.001	0.000	− 0.016	0.002	0.000
Fixed-effects regression									
Overall CSP_KLD	0.001	0.000	0.014	0.002	0.001	0.011	− 0.002	0.003	0.598
Positive CSP	0.000	0.000	0.295	0.000	0.001	0.839	− 0.009	0.004	0.022
Negative CSP	− 0.001	0.000	0.014	− 0.004	0.001	0.002	− 0.010	0.005	0.032
DPD estimation									
Overall CSP_KLD	0.000	0.000	0.779	0.002	0.002	0.301	− 0.002	0.004	0.521
Positive CSP	0.000	0.001	0.377	0.003	0.002	0.163	0.000	0.005	0.970
Negative CSP	0.000	0.001	0.794	0.001	0.002	0.655	0.005	0.005	0.351

Overall CSP_KLD = Overall CSP measured by KLD ratings

Control variables: *R&D intensity*, *R&D dummy*, *advertising intensity*, *advertising dummy*, *firm leverage*, *slack resources*, *firm size*, *firm risk*, *board independence*, *institutional ownership*, *executive total compensation*, *executive long-term compensation*, *CEO duality*, *SOX dummy*, *financial crisis dummy*, *industry dummies*, *and year dummies*

Table 6, the pooled OLS regression shows that positive CSP is positively related to ROA ($b = 0.001$, $p = 0.000$), while negative CSP is negatively related to ROA ($b = -0.001$, $p = 0.000$). In addition, the fixed-effects regression shows that positive CSP is not significantly related to ROA ($b = 0.00$, $p = 0.295$), while negative CSP is negatively related to ROA ($b = -0.001$, $p = 0.014$). However, the DPD estimation shows that positive CSP ($b = 0.000$, $p = 0.377$) and negative CSP ($b = 0.000$, $p = 0.794$) do not have a causal influence on ROA. Together, the results suggest that positive CSP and negative CSP would not have a causal influence on ROA.

Alternative Measures of CFP

Table 6 also reports the empirical analyses with alternative measures of CFP, such as ROE and Tobin's Q. The pooled OLS regression shows that ROE is positively related to overall CSP measured by KLD ratings ($b = 0.002$, $p = 0.000$) and to positive CSP ($b = 0.002$, $p = 0.000$) and negatively related to negative CSP ($b = -0.003$, $p = 0.000$). The fixed-effects regression indicates that ROE is positively related to overall CSP measured by KLD ratings ($b = 0.002$, $p = 0.011$) and negatively related to negative CSP ($b = -0.004$, $p = 0.002$). In addition, ROE is not significantly related to positive CSP ($b = 0.000$, $p = 0.839$).

With respect to Tobin's Q, the pooled OLS regression indicates that Tobin's Q is positively related to overall CSP measured by KLD ratings ($b = 0.015$, $p = 0.000$) and positive CSP ($b = 0.014$, $p = 0.000$) and negatively related to negative CSP ($b = -0.016$, $p = 0.000$). The fixed-effects regression shows that Tobin's Q is negatively related to positive CSP ($b = -0.009$, $p = 0.022$) and negative CSP ($b = -0.010$, $p = 0.032$). In addition, the fixed-effects regression indicates a nonsignificant correlation between Tobin's Q and overall CSP measured by KLD ratings ($b = -0.002$, $p = 0.598$).

A Short Summary of the Causal Influence of CSP on CFP

In summary, both the pooled OLS and fixed-effects regression suggest that some measures of CSP can be significantly correlated with some measures of CFP, although the correlations vary depending on which exact measures of CSP and CFP are employed. However, DPD estimation indicates that all three measures of CSP are nonsignificantly associated with the other two measures of CFP, including ROE and Tobin's Q. For example, DPD estimation indicates that ROE is unlikely to be impacted by overall CSP measured by KLD ratings ($b = 0.002$, $p = 0.301$), positive CSP ($b = 0.003$, $p = 0.163$), or negative CSP ($b = 0.001$, $p = 0.655$). Similarly, DPD estimation demonstrates that Tobin's Q is unlikely to be influenced by overall CSP measured by KLD ratings ($b = -0.002$, $p = 0.521$), positive CSP ($b = 0.000$, $p = 0.970$), or negative CSP ($b = 0.005$, $p = 0.351$). Therefore, we can conclude that CSP might be unlikely to have a causal influence on CFP regardless of the measures of CSP and CFP when endogeneity is addressed by DPD estimation.

Table 7 Empirical results of the causal influence of CFP on CSP

Dependent variable	IV = ROA			IV = ROE			IV = Tobin's *Q*		
	b	Robust SE	*p*	*b*	Robust SE	*p*	*b*	Robust SE	*p*
Pooled OLS regression									
Overall CSP_KLD	4.229	0.753	0.000	1.398	0.287	0.000	0.469	0.060	0.000
Positive CSP	2.296	0.609	0.000	0.696	0.226	0.002	0.303	0.052	0.000
Negative CSP	– 2.664	0.525	0.000	– 0.949	0.217	0.000	– 0.244	0.037	0.000
Fixed-effects regression									
Overall CSP_KLD	1.783	0.742	0.016	0.610	0.242	0.012	– 0.070	0.132	0.297
Positive CSP	0.563	0.541	0.299	0.036	0.180	0.840	– 0.247	0.107	0.021
Negative CSP	– 1.298	0.532	0.015	– 0.603	0.191	0.002	– 0.177	0.084	0.035
DPD estimation									
Overall CSP_KLD	3.110	3.542	0.380	2.922	1.482	0.049	0.179	0.240	0.456
Positive CSP	7.184	3.023	0.017	3.028	1.191	0.001	0.273	0.211	0.196
Negative CSP	0.537	2.303	0.816	– 0.298	0.863	0.730	0.129	0.120	0.282

Overall CSP_KLD = Overall CSP measured by KLD ratings

Control variables: *R&D intensity*, *R&D dummy*, *advertising intensity*, *advertising dummy*, *firm leverage*, *slack resources*, *firm size*, *firm risk*, *board independence*, *institutional ownership*, *executive total compensation*, *executive long-term compensation*, *CEO duality*, *SOX dummy*, *financial crisis dummy*, *industry dummies*, *and year dummies*

The Causal Influence of CFP on CSP

In this section, we present the empirical results regarding the causal influence of CSP on CFP. Similar to analyses of the causal influence of CSP on CFP, here, we also employ three measures of CSP and three measures of CFP. The analytical procedures are similar to the analyses of the causal influence of CSP on CFP, which include the three steps discussed above (Wintoki et al. 2012). In this section, we do not again report the results of the first and second steps. Instead, we focus on the results of the third step, in which we apply pooled OLS, fixed-effects, and DPD estimation to empirically examine the causal relationship between CFP and CSP. Table 7 summarizes the results.

ROA as the Measure of CFP

According to Table 7, when CFP is measured as ROA, pooled OLS regression shows that ROA is positively related to overall CSP measured by KLD ratings ($b = 4.229$, $p = 0.000$) and positive CSP ($b = 2.296$, $p = 0.000$) and negatively associated with negative CSP ($b = -2.664$, $p = 0.000$). The fixed-effects regression indicates that ROA is positively related to overall CSP measured by KLD ratings ($b = 1.783$, $p = 0.016$) and negatively associated with negative CSP ($b = -1.298$, $p = 0.015$) but non-significantly related to positive CSP ($b = 0.563$, $p = 0.299$). The pooled OLS and fixed-effects regression together suggest that ROA is significantly associated with certain aspects of CSP, regardless of the direction of the associations.

However, when DPD estimation is used to address endogeneity, Table 7 reports that ROA is only significantly and positively related to positive CSP ($b = 7.184$, $p = 0.017$). ROA is not significantly related to overall CSP measured by KLD ratings ($b = 3.110$, $p = 0.380$) or negative CSP ($b = 0.537$, $p = 0.816$).

ROE as the Measure of CFP

As shown in Table 7, when CFP is measured as ROE, pooled OLS regression shows that ROE is positively related to overall CSP measured by KLD ratings ($b = 1.398$, $p = 0.000$) and positive CSP ($b = 0.696$, $p = 0.002$) and negatively associated with negative CSP ($b = -0.949$, $p = 0.000$). The fixed-effects regression indicates that ROE is positively related to overall CSP measured by KLD ratings ($b = 0.610$, $p = 0.012$) and negatively associated with negative CSP ($b = -0.603$, $p = 0.002$) but non-significantly related to positive CSP ($b = 0.036$, $p = 0.840$). The pooled OLS and fixed-effects regression together suggest that ROE is significantly associated with certain aspects of CSP, regardless of the direction of the associations.

When DPD estimation is used to address endogeneity, Table 7 reports that ROE is significantly and positively related to overall CSP measured by KLD ratings ($b = 2.922$, $p = 0.049$) and positive CSP ($b = 3.028$, $p = 0.001$). In contrast, ROE is not significantly related to negative CSP ($b = -0.298$, $p = 0.730$).

Table 8 DPD estimation using sustainability scores to measure CSP

Panel 1: Empirical results of the causal influence of CSP on CFP

	DV = ROA			DV = ROE			DV = Tobin's *Q*		
Independent variable	*b*	Robust SE	*p*	*b*	Robust SE	*p*	*b*	Robust SE	*p*
Pooled OLS regression									
Overall CSP_SUS	0.000	0.000	0.054	0.000	0.001	0.437	− 0.006	0.002	0.001
Fixed-effects regression									
Overall CSP_SUS	0.000	0.000	0.221	− 0.001	0.001	0.468	0.004	0.003	0.095
DPD estimation									
Overall CSP_SUS	− 0.001	0.001	0.266	− 0.004	0.003	0.240	− 0.002	0.007	0.812

Panel 2: Empirical results of the causal influence of CFP on CSP

	IV = ROA			IV = ROE			IV = Tobin's *Q*		
Dependent variable	*b*	Robust SE	*p*	*b*	Robust SE	*p*	*b*	Robust SE	*p*
Pooled OLS regression									
Overall CSP_SUS	− 6.580	3.382	0.052	0.825	1.057	0.435	− 0.680	0.211	0.001
Fixed-effects regression									
Overall CSP_SUS	− 3.000	2.328	0.198	− 0.512	0.692	0.459	0.598	0.365	0.102
DPD estimation									
Overall CSP_SUS	0.718	5.774	0.901	− 0.691	1.768	0.696	0.188	0.795	0.814

Overall CSP_SUS = Overall CSP measured by sustainability scores provided by Sustainalytics

Control variables: *R&D intensity*, *R&D dummy*, *advertising intensity*, *advertising dummy*, *firm leverage*, *slack resources*, *firm size*, *firm risk*, *board independence*, *institutional ownership*, *executive total compensation*, *executive long-term compensation*, *CEO duality*, *SOX dummy*, *financial crisis dummy*, *industry dummies*, *and year dummies*

Tobin's *Q* as the Measure of CFP

As demonstrated by Table 7, when CFP is measured as Tobin's *Q*, pooled OLS regression shows that Tobin's *Q* is positively related to overall CSP measured by KLD ratings ($b = 0.469$, $p = 0.000$) and positive CSP ($b = 0.303$, $p = 0.000$) and negatively associated with negative CSP ($b = -0.244$, $p = 0.000$). The fixed-effects regression indicates that Tobin's *Q* is negatively associated with positive CSP ($b = -0.247$, $p = 0.021$) and negative CSP ($b = -0.177$, $p = 0.035$) but non-significantly related to overall CSP measured by KLD ratings ($b = -0.070$, $p = 0.297$). Together, the pooled OLS and fixed-effects regression suggest that Tobin's *Q* is significantly associated with certain aspects of CSP, regardless of the direction of the associations.

However, when DPD estimation is used to address endogeneity, Table 7 reports that Tobin's *Q* is non-significantly related to overall CSP measured by KLD ratings ($b = 0.197$, $p = 0.456$), positive CSP ($b = 0.273$, $p = 0.196$), and negative CSP ($b = 0.129$, $p = 0.282$).

A Short Summary of the Causal Influence of CFP on CSP

To summarize, the pooled OLS and fixed-effects regression suggest that some measures of CFP are significantly associated with some measures of CSP, regardless of the directions of the associations. Moreover, the DPD analyses report that accounting performance (e.g., ROA, ROE) is positively and significantly associated with positive CSP. Therefore, these empirical findings are consistent with the argument proposed by slack resources theory that accounting performance is likely to have a causal influence on positive CSP when endogeneity is addressed by DPD estimation (Waddock and Graves 1997).

Study 2: DPD Estimation Using Sustainalytics Data

Study 1 uses KLD ratings to examine the causal linkages between CSP and CFP. One limitation of Study 1 is that the KLD ratings cover the years 1997–2012, and more recent KLD rating data are lacking. It is possible that the causal linkages may change in more recent years. To address this limitation, Study 2 relies on the sustainability scores of 2009–2018 as the measure of overall CSP (Surroca et al. 2010). The sample consists of 1573 firm-year observations. Sustainability scores are collected from the Sustainalytics database (www.sustainalytics.com). Sustainalytics' sustainability scores assess how well publicly listed companies proactively manage the environmental, social and governance issues that are most closely linked to their business.

To determine the score of a single firm, the environmental, social, and governance performance of the firm is compared with that of peer firms. Notably, sustainability scores do not differentiate positive CSP from negative CSP; thus, Study 2 can only operationalize overall CSP by sustainability scores, which range from 1–100. To be consistent with Study 1, Study 2 also used DPD estimation and the same control variables. The results are reported in Table 8.

The Causal Influence of CSP Measured by Sustainability Scores on CFP

Panel 1, Table 8 reports the results regarding the causal influence of CSP measured by sustainability scores on CFP. While the pooled OLS regression shows a positive and marginally significant association ($b=0.000$, $p=0.054$), both the fixed-effects regression ($b=0.000$, $p=0.221$) and DPD estimation ($b=-0.001$, $p=0.266$) indicate that overall CSP measured by sustainability scores is non-significantly related to ROA. In addition, pooled OLS regression ($b=0.000$, $p=0.437$), fixed-effects regression ($b=-0.001$, $p=0.468$), and DPD estimation ($b=-0.004$, $p=0.240$) show that overall CSP measured by sustainability scores is non-significantly related to ROE. Last, the pooled OLS regression reports a negative and significant association ($b=-0.006$, $p=0.001$), and the fixed-effects regression indicates a positive and marginally significant association ($b=0.004$, $p=0.095$), but the DPD estimation ($b=-0.002$, $p=0.812$) indicates that the overall CSP measured by sustainability scores is non-significantly related to Tobin's Q.

In summary, the DPD estimation suggests that CSP may not causally influence CFP when CSP is measured by sustainability scores. This finding is consistent with Study 1, in which CSP is measured by KLD ratings.

The Causal Influence of CFP on CSP Measured by Sustainability Scores

Panel 2, Table 8 reports the results regarding the causal influence of CFP on CSP measured by sustainability scores. While pooled OLS regression shows a negative and marginally significant association ($b=-6.580$, $p=0.052$), both the fixed-effects regression ($b=-3.000$, $p=0.198$) and DPD estimation ($b=0.718$, $p=0.901$) indicate that ROA is not significantly related to overall CSP measured by sustainability scores. In addition, pooled OLS regression ($b=0.825$, $p=0.435$), fixed-effects regression ($b=-0.512$, $p=0.459$), and DPD estimation ($b=-0.691$, $p=0.696$) show that ROE is non-significantly related to overall CSP measured by sustainability scores. Last, the pooled OLS regression indicates a negative and significant association between Tobin's Q and overall CSP measured by sustainability scores ($b=-0.680$, $p=0.001$), but the fixed-effects regression ($b=0.598$, $p=0.102$) and DPD estimation ($b=0.188$, $p=0.814$) indicate that Tobin's Q is non-significantly related to overall CSP measured by sustainability scores.

In summary, the DPD estimation suggests that CFP may not causally influence overall CSP when overall CSP is measured by sustainability scores. This finding is inconsistent with the results of Study 1, in which accounting performance (i.e., ROA, ROE) may have a positive influence on positive CSP measured by KLD ratings of strengths. However, please note that Study 2 cannot test the influence of CFP on positive CSP due to the limitation of sustainability scores. Accordingly, we might posit that the measurement of CSP and/or CFP matters in the examination of the causal linkages between them.

Discussion

Among the studies on the virtuous circle between CSP and CFP (Busch and Friede 2018; Waddock and Graves 1997), to the best of our knowledge, our study is the first to adopt DPD estimation to examine bidirectional causality when endogeneity is accounted for. The DPD estimation yields two important findings regarding this virtuous circle. On the one hand, our DPD analyses yield empirical evidence implying that CSP may not have a causal influence on CFP, a finding substantially different from what has been reported by prior studies (Margolis and Walsh 2003). On the other hand, our study also implies that accounting performance (e.g., ROA, ROE) is likely to have a causal influence on positive CSP. Although it is beyond the scope of this study to comprehensively explore the explanations for our findings, our study still has several important implications for research.

Implications for Research on CSP

As noted, although numerous empirical studies have examined the CSP–CFP relationship and although a virtuous circle between CSP–CFP has been proposed (Busch and Friede 2018; Waddock and Graves 1997), most of the previous studies suffer from serious endogeneity issues (Crane et al. 2017; Huang and Watson 2015). Therefore, our application of DPD estimation to empirically examine this virtuous circle has an important implication for this line of inquiry. That is, using a well-developed method to account for endogeneity, our study implies that this virtuous circle may not exist. On the one hand, our study implies that there may not be a universal causal linkage from CSP to CFP and casts doubt on the business case for CSP (also see Lee et al. 2018; Zhao and Murrell 2016). As shown by our review, previous studies have mainly argued that CSP causally affects CFP because CSP cultivates more cooperative, favorable, and enduring relationships with stakeholders, which in turn lead to a set of favorable mediating outcomes, such as enhanced reputation, customer and purchase intention, employee job satisfaction, innovation, and reduced risk. Subsequently, those favorable mediating outcomes are expected to improve CFP.

Despite these arguments, our study suggests that a universal causal linkage from CSP to CFP may not exist. One explanation for this is that there are multiple causal mechanisms through which CSP affects CFP and that those mechanisms may not always exist for all firms at all times. It is also possible that the causal influence of CSP on CFP is mediated by several mediators in parallel or sequentially and that such a causal influence is indirect rather than direct. For example, in a recent meta-analysis, Zhao et al. (2020) report that the impacts of CSP on employees' attitudes and behaviors (e.g., job satisfaction, organizational commitment, and turnover intention) can be mediated independently and in parallel by organizational justice, trust, and organizational identification and can also be mediated by those variables in a sequential order. Given that employees' attitudes and behaviors can mediate the influence of CSP on CFP, Zhao et al.'s (2020) findings imply that the causal linkage from CSP to CFP is much more complex than we previously expected. Therefore, we suggest that future studies examining the causal influence of CSP on CFP should focus more on specific mediating mechanisms to explain the causal linkage from CSP to CFP. In fact, in their review paper, Aguinis and Glavas (2012) indicate that only 7% of the studies addressing the outcomes of CSP explored the mediating mechanisms. Given that many mediators have been proposed but few have been tested, we suggest that examining the specific mediating mechanisms can shed new light on why and how CSP causally affects CFP. In addition, it is possible that CSP may complement other variables' effects on CFP. One recent study reports that CSP may moderate the inverted U-shaped relationship between explorative/exploitative innovation and CFP (Zhao et al. 2019). Future studies can also explore whether and how CSP affects CFP by interacting with other variables, such as innovation and corporate governance.

On the other hand, our study implies that accounting performance (e.g., ROA, ROE) is likely to have a causal influence on positive CSP. While previous studies generally agree that better CFP can accrue greater slack resources, they disagree on the effects of different types of slack resources on CSP (e.g., Julian and Ofori-Dankwa 2013; Shahzad et al. 2016; Zhang et al. 2018). To better understand the causal influence of CSP on CFP, future studies can not only examine the specific mediating roles of slack resources but also explore the effects of different types of slack resources on different dimensions of CSP (e.g., positive vs. negative). For example, it would be interesting to determine whether the effects of financial resources and human resources are canceled out when greater financial resources and human resources are accrued by better CFP simultaneously. In addition to slack resources, future studies can explore other mediating mechanisms through which CFP causally affects CSP.

In addition to examining the theoretical mechanisms between CSP and CFP, another potential approach is to examine the moderating conditions. For example, the social expectations of firms have evolved over time, and hence, the CSP–CFP linkage may also have evolved over time. In this view, the CSP–CFP linkage may be positive in one period and become negative in another period. In one study examining the impact of CSP on sell-side analysts' assessments of firms' future financial performance, Ioannou and Serafeim (2015) find that analysts issued more pessimistic recommendations for firms with high CSP in the early 1990s but assessed these firms more optimistically over time. This changing trend in the assessment of CSP suggests that analysts perceived CSP as an agency cost and evaluated CSP negatively in the early 1990s, while they perceived CSP with a stakeholder focus and assessed CSP positively in more recent years. Future studies can continue to examine how other stakeholders' assessments of CSP evolve over time and how this changing trend in turn influences the CSP–CFP linkage.

Last, our study also demonstrates that the measures of CSP, as well as the measures of CFP, are important to the empirical results. Study 2 uses sustainability scores to replicate Study 1, which adopts KLD ratings to measure CSP. Both Study 1 and Study 2 suggest that CSP has no causal influence on CFP. Furthermore, Study 1 reports a positive and significant influence of CFP (i.e., ROA, ROE) on CSP, while Study 2 reports a nonsignificant relationship. The idea that using different assessment metrics of CSP and CFP can yield different empirical results is not new (Chatterji et al. 2016), and we further argue that examining the specific causal mechanisms with specific measures can yield a new understanding of the causal linkage between CSP and CFP.

In summary, we argue that future studies should continue to examine the bidirectional causality suggested by Busch and Friede (2018) but should focus more on the specific mediating mechanisms through which CSP causally influences CFP or through which CFP causally affects CSP. Ullmann (1985) suggests that there is no discernable relationship between CSP and CFP because there is no good reason—no theory—to connect CSP and CFP. However, we suspect that reasonable mediating mechanisms can provide good reason and good theory to explain why CSP and CFP are causally linked. In addition, we posit that the mechanisms by which CSP influences CFP might be different from the mechanisms by which CFP affects CSP. We argue that examining the unique mechanisms through which CSP affects CFP or through which CFP influences CSP can enrich our understanding of the causality between CSP and CFP.

Implications for Management and Organization Research

Management and organization researchers have increasingly recognized the importance of theorizing and examining causal relationships and have considered causality as critical as novelty in theoretical development. As argued by Cornelissen and Durand (2012: 153), "a real obligation… is to identify whether… we generate novel theorizations in terms of the underlying causal relationship—and this is arguably more important than just pinpointing gaps or proposing novel suppositions" (Alvesson and Sandberg 2011). In this paper, we document the usefulness of DPD estimation in addressing endogeneity, a core challenge of empirically establishing causal relationships (Hamilton and Nickerson 2003; Shaver 1998). Because many management and organization studies are not conducted in natural, quasi-natural, or controlled experimental settings, and in many situations, identifying valid external instrumental variables is not an easy task, scholars may use DPD estimation as a feasible method to address endogeneity and to yield a better estimate of the causal influence of one variable on another variable. For example, the influence of corporate governance (e.g., compensation and ownership structure) on firm performance has been studied for decades, but the empirical findings regarding this relationship are mixed and suffer from the problem of endogeneity (Dalton et al. 2007). Thus, researchers can use DPD estimation to yield a better understanding of the causal linkage between corporate governance and firm performance.

Practical and Managerial Implications

Advocates of CSP have long proposed a virtuous circle between CSP and CFP (Busch and Friede 2018); e.g., doing good leads to doing well, and doing well also results in doing good (Waddock and Graves 1997). Our study directly tests this virtuous circle. More specifically, we conduct two studies to examine the causal relationship between CSP and CFP. Study 1 relies on KLD ratings to measure CSP. While the results of Study 1 imply that accounting performance may have a causal impact on certain aspects of CSP, these results cast doubt on the existence of an overall causal linkage between CSP on CFP. Study 2 uses sustainability scores to measure CSP. Study 2 reports that CSP does not causally influence CFP and that CFP does not have a causal impact on CSP. Together, Study 1 and Study 2, using different measures for CSP, suggest that a virtuous circle between CSP and CFP may not exist. Therefore, managers and practitioners cannot simply assume that doing good will necessarily lead to doing well and that doing well can naturally result in doing good. Instead, managers and practitioners should seriously consider the causal mechanisms through which CSP may influence or be influenced by CFP. Without a deeper understanding of those causal mechanisms, managers and practitioners cannot guarantee that investments in CSP generate positive CFP, and thus, they should be very cautious in their CSP investments.

Limitations

Despite the advantages of DPD estimation, our study applying this method also has limitations. First, one critical assumption of DPD estimation is that any time-varying variables influencing both CSP and CFP are included as control variables (Hansen and Singleton 1982); otherwise, DPD estimation will be biased. However, this assumption seems to be unrealistic because we could not include all time-varying variables that could possibly affect both CSP and CFP in our empirical model. To address this assumption, we refer to previous studies to identify as many time-varying variables as possible that can potentially affect both CSP and CFP and then incorporate them as control variables. However, it is still possible that some time-varying variables that influence both CSP and CFP are omitted and that the DPD estimation results are therefore still biased. However, one should note that traditional estimation methods, such as OLS and fixed-effects regression, also suffer from the problem of omitting time-varying variables. Therefore, we argue that the results of DPD estimation are still better than those of traditional estimation methods.

The violation of the assumption noted above leads to a second limitation of our study. According to Wintoki et al. (2012), when time-varying variables are omitted, the AR(2) test and the Hansen *J*-test are unable to correctly examine whether the instrumental variables are exogenous. To address this problem, Wintoki et al.'s (2012) simulation shows that the power of the Hansen *J*-test increases with sample size. In addition, the power of the Hansen *J*-test greatly increases when instrumental variables are "collapsed." Our study has a sample of 9028 firm-year observations, and we "collapse" instrumental variables when applying DPD estimation; therefore, using the Hansen *J*-test in our study may not be a problem. However, we acknowledge that the presence of omitted time-varying variables influencing both CSP and CFP may weaken the power of the AR(2) test and that we have not fully addressed this issue in our study.

Third, we note that DPD estimation cannot address all endogeneity issues in the estimation of the causal relationship between CSP and CFP. When available, natural experiments are still the "gold standard" for examining causal influence. However, scholars may continue to rely on archival and observational data to examine the causal relationships because natural experiments (e.g., natural disasters) do not occur frequently. In this sense, DPD estimation can still be a feasible alternative.

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